N89-15582

AUTOMATIC INSPECTION OF ANALOG AND DIGITAL METERS IN A ROBOT VISION SYSTEM*

Mohan M. Trivedi
Suresh Marapane
ChuXin Chen

Electrical and Computer Engineering Department
The University of Tennessee
Knoxville, TN 37996-2100

ABSTRACT

A critical limitation of most of the robots utilized in industrial environments arises due to their inability of utilize sensory feedback. This forces robot operation in a totally preprogrammed or teleoperation modes. In order to endow the new generation of robots with higher levels of autonomy techniques for sensing of their work environments and for accurate and efficient analysis of the sensory data must be developed. In this paper detailed development of vision system modules for inspecting various types of meters, both analog and digital, encountered in a robotic inspection and manipulation tasks are described. These modules are tested using industrial robot having multisensory input capability.

1. Introduction

Advanced robotic systems capable of performing a variety of tasks in complex unstructured environments will have to possess sophisticated sensory capability for acquiring information about their work environments. Also required is the associated capability for analyzing such information in an accurate and efficient manner. Robotic system with sophisticated sensory capability will be of particular utility in tasks such as automated assembly [5], inspection and manipulation in hazardous environments such as nuclear plants, [7] or space based platforms. Types of sensors which can be utilized in such systems include vision, range, proximity, tactile, force and torque, etc. [3]. Of these, vision sensory modality is recognized as the one providing rich characterization of work environment with various types of relatively inexpensive and well engineered camera systems.

The specific area of research reported in this paper deals with a vision system that has been designed and developed to perform various inspection and manipulation tasks associated with a control panel. The panel contains a number of displays, both analog and digital, and controls like switches and valves. In addition to the above panel the test bed for our research includes an industrial robot capable of sensing the environment with vision, range, proximity, force and torque and touch sensors. The main tasks performed by the vision system include: automatic location of the test panel, positioning of the robot arm to acquire appropriate input images of the panel, automatic recognition of all objects

*This research is supported by the Advanced Technology Development Division of the U. S. Department of Energy under grant No. DOE DE-FG02-86-NE31968.

appearing on the panel and determination of their 3-dimensional location. Once the objects are located the system has to acquire finer resolution images of individual objects to determine their status. In this paper we shall present the detailed procedure developed to "read" various types of analog and digital meters. The paper includes results of several experiments carried out to verify the robustness of the system in performing automatic inspection and manipulation tasks. It is believed that the robot vision system can be utilized to perform tasks in a number of application domains including space.

2. Vision Guided Robotic Inspection and Manipulation

The main goal of a robot vision system is to provide an accurate interpretation of a scene utilizing images of the scene as the primary source of input. The interpretation can be provided in a variety of forms and at different levels of abstraction. A useful form of interpretation may include an object location map where different types of physical objects appearing in the scene are independently recognized and accurate locations of these objects in the scene are determined. Also, of utility is the information regarding the status or condition of an object. Design of a computer vision system that can perform such object recognition and scene interpretation is a complex and challenging task. The main difficulty underlying the task comes from the fact that images are 2-dimensional projections of the 3-dimensional real scene and innumerable combinations affecting the illumination source, scene and sensor parameters can result in the same observable value of recorded image intensity.

In order to make the above problem computationally tractable model-based approach to computer vision is proposed [6]. The approach requires knowledge of a series of models associated with objects which are believed to appear in the scene. These models can be recorded in the knowledge-base of the system. Various features from the input images are extracted by using low- level, general purpose operators. These operators should be robust in extracting image features containing meaningful information about the objects. Finally, a correspondence is sought between the image derived features and scene domain models to recognize the objects. This is accomplished by utilizing various decision making schemes in the matching module.

Development of autonomous systems for a variety of applications in an industrial environment will require major research efforts to resolve many complex issues. We have undertaken an approach, which we believe allows making incremental progress towards the eventual development of such a system. Our initial research effort is directed towards researching issues associated with acquisition and analysis of multiple sensory data using a robotic system. This is accomplished by focusing on the development of an autonomous system that is capable of performing various inspection and manipulation tasks associated with a typical panel. For example these tasks can range from reading of various meters and displays, operating different types of switches and controls. Also, included are tasks associated with valve operation. Teleoperation or automatic operation of valves in nuclear power plants is recognized as one of the important desired capabilities of a robotic systems. Design of the panel was done in consultation with a team from a nuclear power plant developer, using all "off-the-shelf" components. Our experimental set-up includes a test panel, a robot having multiple sensory capability, computers, and various manipulation tools. The test panel and the robot with various sensors mounted on the arm are shown in Figure 1.

Typical autonomous robot operation will involve the following. The robot first identifies the exact geometrical position of the panel using a camera calibration program. Next it uses a computer vision system to develop an object location layout map for various devices appearing in the panel. The task command for the robot is provided through the binary coded lights of an LCD display. After decoding the command the robot performs requested inspection or manipulation task.

Robustness and ease in expandability to accomodate changes in the task environment are two key features guiding the development of the vision system. The system is compartmentalized in two basic groups of procedures. The first group consists of general purpose procedures for camera calibration, image acquisition, knowledge acquisition, image segmentation, matching, and robot arm movements. The second group consists of special purpose procedures mainly designed for determining status of individual objects.

3. Recognition of Object Status

Depending upon the type and nature of the object the camera mounted on the arm is moved to take images using orthogonal viewing geometry. These images are analyzed to determine the status of the object. The objects appearing on the test panel and the type of status information associated with each one of them are listed in Table 1.

Table 1. List of objects appearing on the test panel and their status information.

OBJECT TYPE	STATUS
1. Light	On/Off
2. Analog Meter	Needle Reading
3. Digital Meter	7-Segment Code
4. Valve	Position of the Holes
5. Slider Control	Position of the Sliding Arm
6. Push Button Switch	On/Off
7. Toggle Switch	On/Off

In order to account for changes in the task environment one will require an additional knowledge acquisition session to update the knowledge base and incorporation of the appropriate routines to determine the status information of the objects added to the knowledge base.

Status recognition of three object types are considered in this paper. They are two types of analog meters and digital (LCD) meter. Once the objects are identified by the object recognition module further processing is required to recognize their status. The primary requirements of the object status recognizers are their robustness, accuracy, and speed. Incorporation of limited apriori knowledge about the objects greatly facilitate in meeting these requirements.

3.1 Reading an analog meter of type I

The main task in reading an analog meter is the determination of its needle orientation with respect to the horizontal direction. Once this angle is determined, the knowledge of the total swing angle of the needle for Full Scale Deflection(FSD) and the range of the meter enables one to compute the meter reading. It is assumed that the meter scale is symmetrical about the the vertical and that it is linear with respect to the angle. This assumption holds for many types of commercially available analog meters.

In this section it is assumed that the analog meter has been isolated from the rest of the image by the segmentor, and all further processing is performed within a window containing only the analog meter. The approach consists of two major steps.

The first step is the extraction of edges. For this, Marr edge detector [1] is chosen since it generates one pixel wide, closed contours. Since one can assume without loss of generality that the needle of a meter is a linear feature, the next step involves the analysis of all linear features within the processing window. For this, we choose Hough transforms [2]. The advantage of using Hough transforms includes it's relative insensitivity to noise and to gaps in the image of a line. This makes the procedure less sensitive to the results of the edge detector. In the slope-intercept representation of a line, however, the Hough parameter space becomes unbounded due to the slope and intercept becoming infinite for vertical lines. Since a bounded parameter space is desired for the analysis, a normal representation of a line is often used. In this representation the parameters are ρ and θ and

$$x \cos\theta + y \sin\theta = \rho \tag{1}$$

The parameter θ can be considered to be bounded between -θ_1 and θ_2. These angles are not required to be known exactly but the range needs to accomodate the total swing (i.e. all possible orientations) of the needle. Thus,it is reasonable to assume that this range of the parameter θ is known for a particular analog meter. Also, parameter ρ is bounded by the length of the meter. This implies that the parameter ρ is bounded in the range 0 to length of the processing window,w, known from the object recognition module. Therefore the analysis of linear features only requires to be performed within the bounded parameter space -θ_1 to θ_2 and 0 to w.

In the step 2, following edge detection, the linear feature analysis is performed within the bounded space -θ_1 to θ_2 and 0 to w. An implication of this quantization range of θ is that the horizontal linearities ($\theta = 90^o$) are not contained within the parameter space and therefore the horizontal edges are eliminated from further consideration. The elimination of false vertical linearities, linearities that does not correspond to the needle, is more involved since the needle itself may be vertically oriented. The key to the elimination of these false linearities is the observation that the vertical features that do not correspond to the needle have a ρ value which is either closer to 0 or w. Thus, seeking a local maxima, (θ_n, ρ_n), in the parameter space away from $\rho = 0$, say $\rho = 0 + \Delta_\rho$, and away from $\rho = w$, say $\rho = w - \Delta_\rho$, where Δ_ρ is a small number, will guarantee that the maxima is indeed due to the linearity of the needle.

Figure 2 shows a sequence of processing steps for an image where the analog meter occupies less than 2% of the total area of the image. The robustness of the procedure is clearly demonstrated in this experiment.

The accuracy of the final result is directly dependent on the accuracy of the angle of orientation of the needle. Hence, the accuracy of the result is dependent on the resolution of the parameter θ in the parameter space. In the experiments shown in this section the parameter θ was quantized to an 1 degree resolution. Since the analog meter had a resolution of 0.2 volts/degree this quantization results in a resolution of 0.2 Volts in the meter reading. This accuracy of the reading can be increased by finer division of the parameter θ at the cost of increasing execution time.

3.2 Reading an analog meter of type II

In this type of meters the needle is not pivoted at one end, but the needle moves across a horizontal scale. Thus, reading the meter requires determination of the needle position with respect to the left edge of the scale. Knowing the total length of the scale, L_s, the range of the meter, x_0 to x_f, and the needle position, l_s, the meter reading, x_r can be computed as:

$$x_r = \frac{x_f - x_0}{L_s} l_s + x_0 \tag{2}$$

In practise however, the lengths L_s and l_s can not be derived from the images since the segmentor can not isolate the inner scale from the rest of the meter. This requires reformulation of equation (2) using the derivable distances w, length of the meter(window), and l_w, the needle position with respect to the left edge of the meter(window). Using these distances x_r can be found as,

$$x_r = \frac{x_f - x_0}{w} l_w + x_0 - error \tag{3}$$

This error term can be computed using an image reading a known value, say x_0. In this case ,equation(2) will yield

$$error = \frac{x_f - x_0}{w} l_0 \tag{4}$$

Since the needle is a linear vertical feature, the analysis of linear features applies to this task as well. The detection of the needle requires only a minor change in the linear feature analysis step of the section 3.1. Now the Hough parameter θ is bounded between $0 - \Delta_\theta$ and $0 + \Delta_\theta$, where Δ_θ is a small angle. Notice that the $\theta = 0^o$ corresponds to a vertical line. The bounds of the parameter ρ remains the same as in section 3.1, i.e., between 0 and w. This range of θ eliminates the horizontal features and the false vertical features are eliminated using the same rule of section 3.1, i.e., the local maxima in parameter space is required to be away from $\rho = 0$ or $\rho = w$.

Under these constraints, the local maxima ,(θ_n, ρ_n), will indeed correspond to the needle and $l_w = \rho_n$. Now we can compute the meter reading x_r using equation(3), if the error term has been previously computed as explained by equation(4).

The sequence of steps involved in processing an 128X128 image is illustrated in Figure 3. The original image is shown in Figure 3(a) and Figure 3(c) shows the line corresponding to the maxima in Hough space superimposed on the edge map (Figure 3(b)). These results suggests that the presented procedure is an effective method for reading this type of analog meters, provided that the algorithm can be trained for computing the error term in equation (3) using an image of known meter reading. The accuracy of the result is now dependent on the quantization of the parameter ρ.

3.3 Reading a digital (LCD) meter

This task actually consists of two recognition tasks. First, the digits needs to be identified, and secondly the decimal number represented by the individual digits needs to be identified. For recognition of digits we choose to use Fourier descriptors [4] for its size and rotational invariance properties. Once the individual digits are identified the decimal number is formed using an *ad-hoc* procedure explained in the next section.

As in the previous sections we assume that the processing is performed within a window containing the digital meter. Since the digits are best discriminated using their edge properties, the first step in processing is the extraction of edges. In order to represent the structural shape of the objects in a suitable form for the Fourier descriptors, this step is followed by a thinning process. In this step we use a modification of an algorithm developed by Zhang and Suen [8], for skeletonizing the edges. This algorithm is known to have some inherent drawbacks. One of the problems was due to the total elimination of small regions during the skeletonizing process. This limitation can however be overcome by simple modification.

In order to use the Fourier descriptors to identify the digits we require the digit to appear as a single object, i.e. consisting of connected segments. However, it was observed that in the 7-segment display the vertical segments do not appear to be connected unless the middle horizontal segment is lit. Figure 4(a) shows the edge map of digits 0,1 and 7 in which the the digits do not appear as a single region due to the above. Therefore, the edge map was pre-processed before skeletonizing to fill the gaps between the vertical segments. Since we are primarily concerned with the breaks between vertical segments, the pixels labelled X and Y are required to be non-edge pixels. The mask is centered on non-edge pixels and if the number of edge pixels in the top part of the mask ($P_0 - P_5$) and the bottom part of the mask ($P_6 - P_{11}$) both exceeds a particular threshold (in our application we use a threshold of 1) then the center pixel was flagged to be an edge pixel. This procedure is performed asynchronously, i.e. the breaks are not filled until all the pixels have been considered.Figure 4(c) shows the results of performing the filling on Figure 4. The skeleton of Figure 4(c) is shown in (d).

In step 4, we use Fourier descriptors to recognize the objects within the processing window. This step uses prototypes of all 10 digits, pre-stored in a data base, for classification. Objects not matching any of the 10 prototypes to a higher degree is classified as unknown. In addition to recognizing the objects we also determine the minimum enclosing rectangle of each of the object. This information is used in identifying the position of the object within the window. Also computed is the area of the object. This is required to discriminate between the digit 0 and 8 since the Fourier descriptors are unable to discriminate between them. At the end of this step all objects within the processing window have been identified as a digit or an unknown. This completes the first task of identifying the digits.

The next step is the formation of the decimal number from the individual digits identified within the window. In step 5, the objects within the window is processed from the rightmost object to the leftmost object using the above rules where necessary. The rightmost object is determined using the coordinates of the minimum enclosing rectangle.

Illustrated in Figure 4 are the sequence of processing steps for an 128X128 image. Since the recognition task is performed on edge maps of the image, for this procedure to perform error free, the edges needs to be generated correctly. This heavy dependence on the edge detector results limits the minimum size of the image. It was experimentally found that the LCD meter should occupy at least 15% of the total area to guarantee correct results.

4. Concluding Remarks

In this paper we describe development of modules associated with a robotic vision system for automatic inspection and manipulation tasks. The vision system consists of two groups of processing modules. The first comprises general purpose object recognition modules whereas the second comprises of specialized object status recogntion modules. Detailed development of modules for inspecting various types of meters, both analog and digital, is described.

REFERENCES

1. Ballard, D. H. and C. M. Brown, *Computer Vision*, Prentice-Hall, New Jersey, 1982, pp. 123-131.

2. Hough, P. V. C., "Methods and Means for Recognizing Complex Patterns," U. S. Patent 3,069,654, Dec. 1962.

3. Kak, A. C. and J. S. Albus, "Sensors for Intelligent Robots," Handbook of Industrial Robotics, (S. Y. Nof, Editor), John Wiley & Sons, New York, 1985, pp. 214-230.

4. Persoon, Eric and King-Sun Fu, "Shape Discrimination Using Fourier Descriptors," *IEEE Transc. on Systems, Man, and Cybernetics*, Vol. SMC-7, No. 3, March 1977, pp.170-179.

5. Sanderson, A. C. and G. Perry, "Sensor-Based Robotic Assembly Systems: Research and Applications in Electronic Manufacturing," *Proceedings of the IEEE*, Vol. 71, No. 7, July 1983, pp. 856-871.

6. Trivedi, M. M., C. Chen, and S. Marapane, "A Vision System for Robotic Inspection and Manipulation," *Proc. of the Applications of Artificial Intelligence VI Conference*, SPIE Vol. 937, April 1988.

7. White, J. R., R. E. Eversole, K. A. Farnstron, H. W. Harvey, and H. L. Martin, "Evaluation of Robotic Inspection Systems at Nuclear Power Plants," NUREG/CR-3717, U. S. Nuclear Regulatory Commission, Washington, D.C., March 1984.

8. Zhang, T. Y. and C. Y. Suen, "A Fast Parallel Algorithm for Thinning Digital Patterns," *Communications of ACM*, Vol. 27, No. 3, March 1984, pp. 236-239.

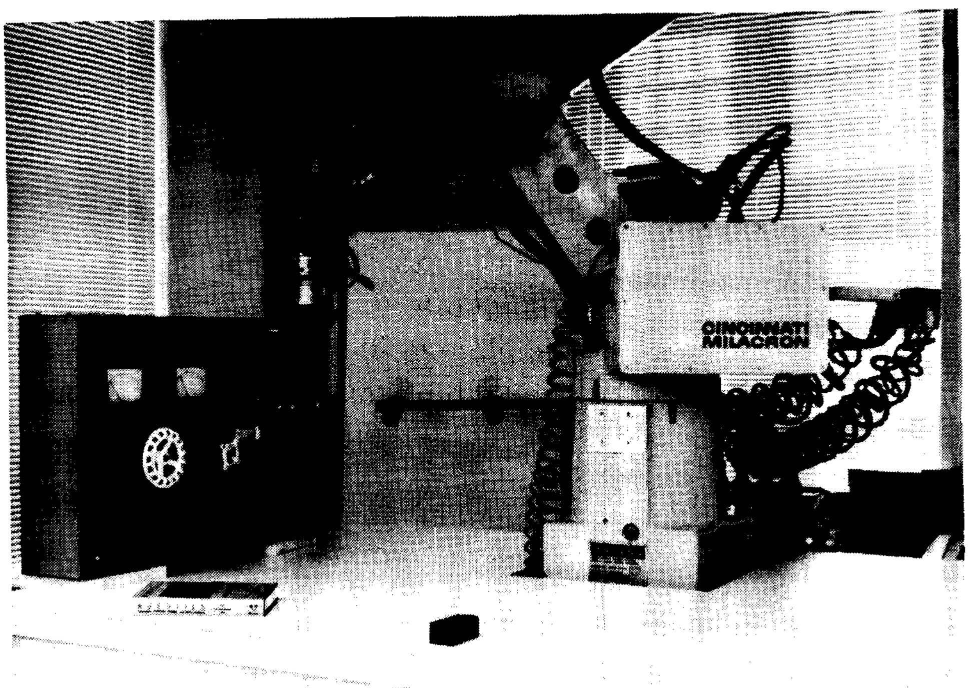
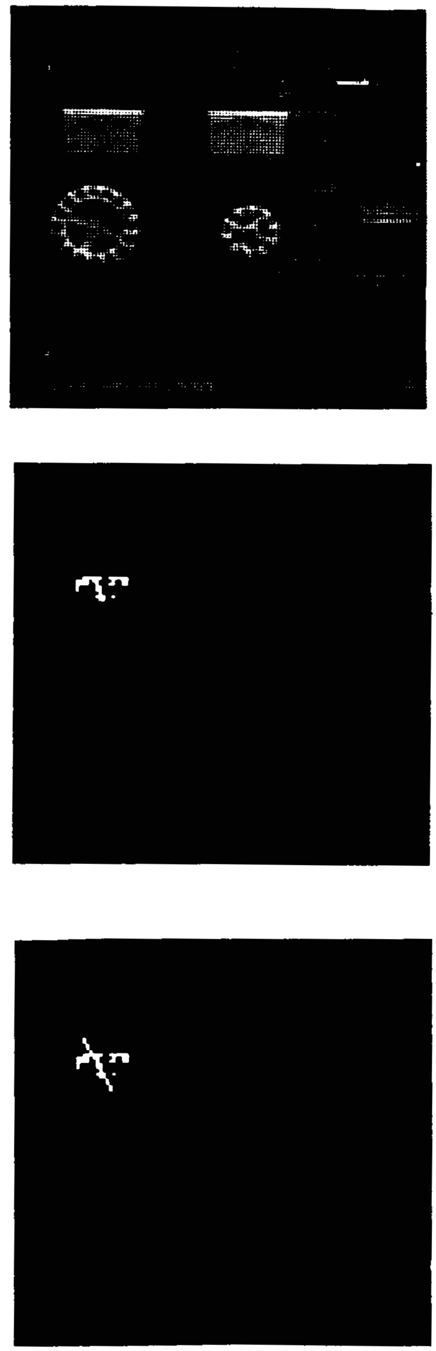


Figure 1: The test-panel and an industrial robot with vision, range, touch, force, and proximity sensory capabilities. The test-panel includes variety of displays, meters, valves, controls, and switches.



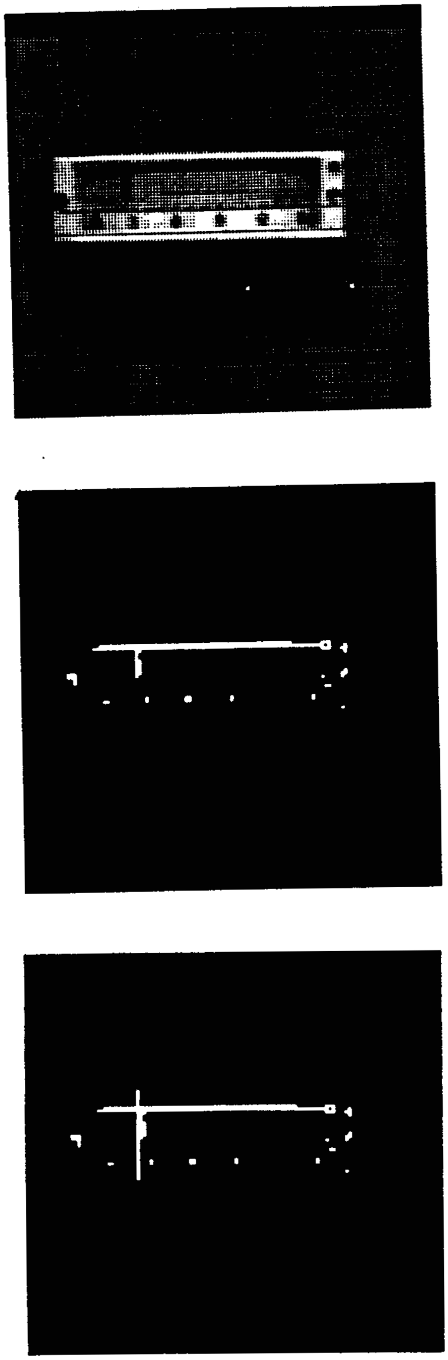
a

b

c

Figure 2: Sequence of processing steps. (a) original image, (b) edge map (9×9 mask) of (a), (c) detected needle superimposed on (b).

ORIGINAL PAGE IS
OF POOR QUALITY



a

b

c

Figure 3: Sequence of processing steps. (a) original image, (b) edge map (5×5 mask) of (a), (c) detected needle superimposed on (b).

ORIGINAL PAGE IS
OF POOR QUALITY

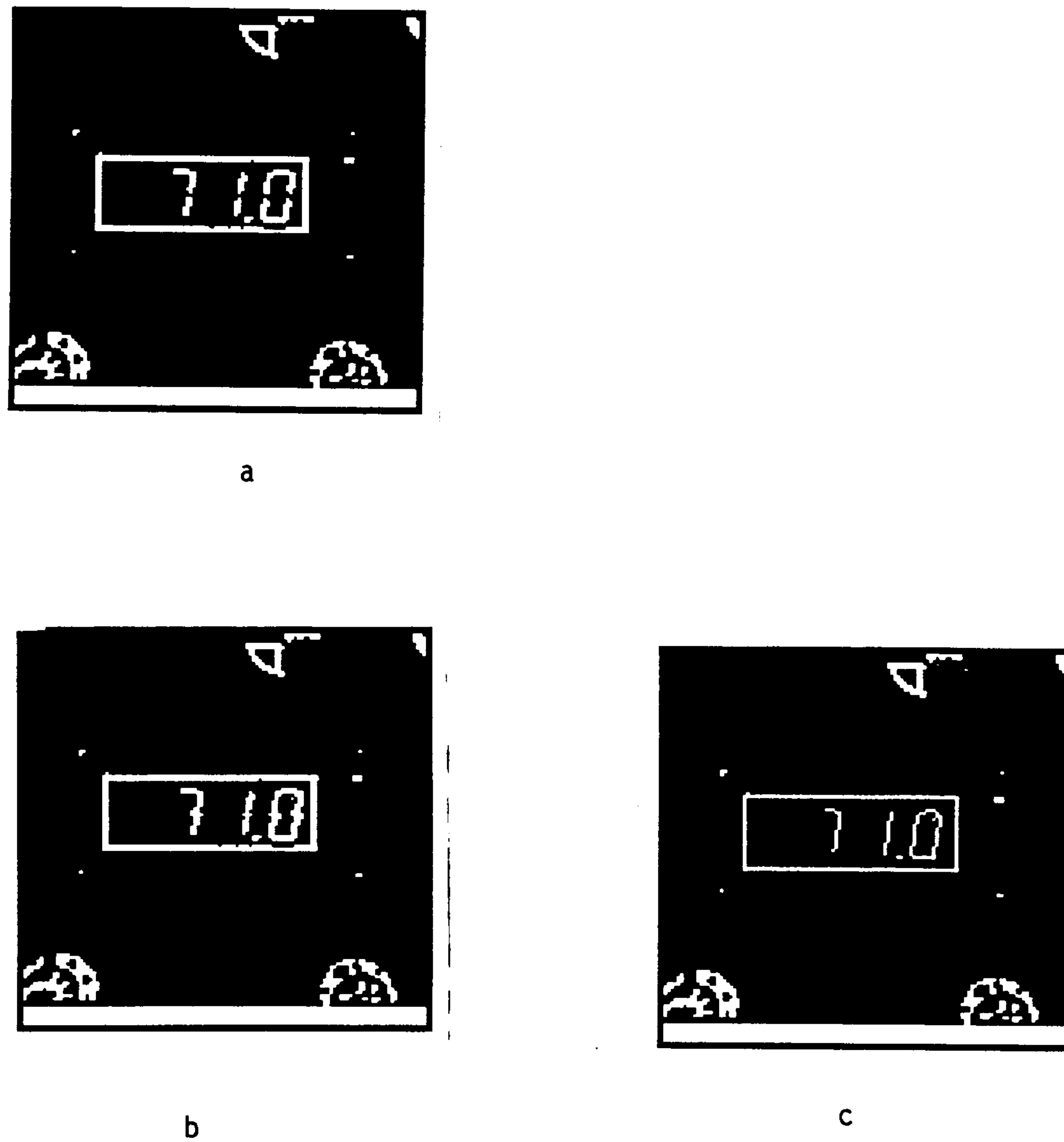


Figure 4: Sequence of processing steps. (a) Typical edge maps of digits 0,1, and 7, (b) Results of filling, (c) Skeleton of (b)